Colour, Count and Speed Identification of a Vehicle for Road Surveillance

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Abstract - The information about a vehicle is very helpful for road surveillance and many applications of city public security. This paper presents different vehicle property detection system for road videos or images. Here is the method for detecting vehicle from urban road video along with its speed, count and color. By tracking every passing vehicle, the color and speed of them are recognized. The vehicle has its specific inner structure and different parts may be in different colours, it requires recognizing the dominant color of a vehicle. So it is very important to select the Region Of Interest (ROI) of detected vehicle portion of the image. After selecting ROI, feature context based color identification method used here. A newly efficient technique based on feature point of vehicle used for vehicle tracking and speed detection. Frame based vehicle counting system improves the performance of the system. The efficient and extensive experiments on both road image and video data demonstrate the potential of the proposed method in intelligent transportation system.

Index Terms – Region Of Interest(ROI), Feature Context(FC), Intelligent Transportation System(ITS)

I. INTRODUCTION

This paper belongs to the main area image processing. It can be defined as a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. The subarea is object recognition that plays a fundamental role in video surveillance systems, military applications, transportation systems, gaming systems, etc. In an object recognition system the objects in the real world from an image of the world are extracting, using object models which are known a priori. In this work the detected object is vehicle from the road video or image. Vehicle detection is a process of detecting the presence or absence of a vehicle in the video sequence. Vehicle tracking is defined as finding the location of a vehicle in each frame of the video sequence. Typically the result of detection is used as initialization process for tracking. Vehicle detection and tracking approaches can be broadly classified based on the representation of the object/vehicle, detection methods and tracking methods.

Fig 1 shows the vehicle boundary recognition by removing road background. Representations of vehicles for detection and tracking include points, shapes, silhouette, contours, and object models. Some of the initial approaches to vehicle detection and tracking systems involve spatial, temporal or spatiotemporal analysis of video sequences. Vehicle colour recognition in natural scenes can provide useful information in vehicle detection, vehicle tracking and automatic driving system.

Fig.1. Vehicle Boundary detection

In this work the colour features are collected from image patches. Then, a classifier is trained for colour recognition. Every vehicle has its specific inner structure, the main challenges in vehicle colour recognition is to select the region of interest (ROI) for recognizing its most dominant colour. Here is a method to implicitly select the ROI for colour detection. To overcome the influence of image quality degradation, preprocessing is performed. The ROI in vehicle images are selected by assigning the sub regions with different weights that are learned by a classifier trained on the vehicle images. After that for its high efficiency and high precision train the classifier by linear support vector machine. This system tracks every passing vehicle for several frames, and obtains the speed of every passing vehicle. The counter based vehicle counting...
improves the performance of vehicle surveillance system.

II. RELATED WORKS

Different vehicle property detection methods are becoming increasingly popular for their high performance, good robustness and easy operation, which have been applied to many fields (such as intelligent transportation systems, visual recognition and vehicle detection).

Localizing their positions in images/videos is an essential step before recognizing the colors and other properties of vehicles. Many of the well-known detection approaches [2]–[5] are used to provide an accurate bounding box for every vehicle in the road image. Thus, the color recognition had performed in the detected bounding boxes of vehicles. In this method, both training and testing images are collected by a vehicle detector from road videos. In object or image colour recognition, the color features are collected from image patches. Then, a classifier is trained for color recognition from those images. The efficiency of multiple support vector machine (SVM) recursive feature elimination for feature selection in the classification of lip color investigated by Wang [6]. These methods are not being applied to the task of vehicle color recognition due to the lack of region-of-interest (ROI) selection. The bag-of-word (BoW)-based methods [11]–[13] describes the spatial information of object and scene. It can be, adopt the framework of BoW in this method. These Bag of Word methods is first used in object and scene retrieval by Sivic and Zisserman [14]. The original features are encoded by a codebook, which is learned from a set of features by a clustering algorithm. Lazebnik [15] extended the original Bag of Word method with new technique called spatial information motivated by the classic and traditional shape descriptor shape context [16]. Feature context (FC) proposed by Wang [13], which divides an image into several fan-shape-like sub regions in a log polar coordinate system. This technique is combined with radial basis coding (RBC) [13] and reference points, Feature Context outperforms spatial pyramid matching (SPM) [11] in scene categorization. All these BoW-based methods focus on scene recognition in the videos. In this present application, by setting multiple reference points, Feature Context can generate many subregions with the irregular shapes on a vehicle portion. Then train a linear SVM as this classifier.

Many video-based traffic data collection has been an area of interest in intelligent transportation system for the past few years. Michalopoulos [17] introduced the very useful autoscope system which has been widely used for traffic data collection. Older video detection systems are effective for collecting macroscopic traffic parameters such as flow, mean speed and density. Further researches about collecting microscopic traffic characteristics and vehicle classification emerge. Former studies by Li [18] introduced an efficient video-based collection system for multi-type vehicles in traffic data. Yuan [19] performed a computer vision system composed of five models for vehicle classification including length-based classification and others. The various experiments showed that some geometric parameters of vehicles such as length, width and height are very useful for classification. Scientist Gupte [21] used regions to detect, track and classify vehicles. But the accuracy was affected by occlusions and shadows. Zhang [20] was placed a virtual detection loop on each lane to extract the pixel-based vehicle length. Then simply divide the vehicles into long vehicles and short vehicles. Unfortunately, sometimes their system cannot detect the cross-lane vehicles and it was insufficient for classification by only using vehicle length because of the errors caused by longitudinal occlusions. Vehicle occlusions are very frequent in the video-based traffic data collection system, which create a detrimental impact on the system accuracy [22].

In general, these previous researches still have the following shortcomings: (i) Some detection systems ignore about detecting cross-lane vehicles and may repeatedly count a vehicle. (ii) The robustness and reliability of object detection is not stable. (iii) The accuracy of classification is obviously affected by vehicle occlusions. (iv) Some classification methods need to collect image samples for learning to classify vehicles, so the classification is obviously affected by the environment and shooting style. The system described in this study makes efforts to overcome these shortcomings. First, a colour image-based adaptive background subtraction is proposed to improve the reliability of object detection and a series of processes like shadow removal and setting road detection region are used to improve the system robustness. Second, some cross-lane virtual detection loops are set up to detect the cross-lane vehicles and a special counting limit is used to avoid the repeated counting. Third, the space occupation of
the blob and data fusion is used to reduce the classification errors caused by vehicle occlusions. Finally, the geometric parameters of vehicles are exploited for classification, so the classification method is universal and does not need training and learning.

III. METHODOLOGY
In this section, the major implementation techniques of the system are described.

A. System Overview
The one-way traffic on urban road lanes is monitored and vehicle properties are detected. The system consists of six modules: user input, vehicle boundary detection, preprocessing, vehicle color detection, vehicle counting and vehicle speed tracking. The Fig. 2 shows the architecture of the system.

B. Vehicle Video Input
The typical urban road videos are captured and used as the input of the vehicle surveillance system. The video input is divided into image frames and processed by the system.

C. Vehicle Boundary Detection
The video is subdivided into image frames. From each image frame the vehicle object is detected and represented using a bounding box. The vehicle background is removed from the image. It is important to extract the accurate initial background for background subtraction and vehicle detection. Before recognizing the colors of vehicles, localizing their positions in images/videos is an essential step. The process of extracting moving foreground objects (input image) from stored background image (static image) or generated background frame form image series (video) is called background subtraction, after that, the extracted information (moving objects) is resulted as the threshold of image differencing. This method is one of widely change detection methods used in vehicle regions detection. The non-adaptively is a drawback which is raised due to the changing in the lighting and the climate situations. A significant contribution suggested the statistical and parametric based techniques which are used for background subtraction methods. After that, the pixel values updated by the Gaussian probability distribution model these pixels. Thus, the color recognition is performed in the detected bounding boxes of vehicles.

D. Preprocessing
The quality of the images/videos taken by the cameras on urban roads is usually poor due to the impact of haze, strong light, and color. Shift caused by bad weather conditions or inappropriate configuration of equipment. The poor quality is a challenge for color recognition. In order to overcome the influences, here adopt the haze removal method and color contrast method as the preprocessing in this method. The original image is under thick haze that makes the color of the vehicle biased to gray. After the haze removal, the image is much clearer. The quality of the image can be improved further using a color contrast stretch. Then applies haze removal first in the preprocessing, since the color contrast stretch cannot significantly improve the quality of the images under thick haze. The dominant color of the vehicle image is more obvious after the haze removal algorithm and the color contrast stretch method.

E. Vehicle Color Detection
Different color features of patches are extracted from the enhanced images. For side-view vehicle images, the model trained from the frontal view may not make the correct predictions due to the different structure of the Region Of Interest (ROI). Following is the framework of Feature Context.

The patches are sampled into different frame like structures. This can be denoted as P= \{p1, p2, p3..., pn\}. Every patch feature is encoded with vector v. The vector is \( C(P) = v_1 \ldots v_k \). The value of every patch is denoted using histogram ribbons. Take a reference point \( r \) in image \( I \). Log polar coordinate system, \( l = I \ldots R \) and the polar angle \( \theta = \pi/N \). R is the bin radius and N is the number of color bins. FC representation of Reference point \( r \) is as follows.
FC(r, l, 0, i) = N \{ r^i \} .................................(1)

Here N is the pooling function obtained from color code book and I is index of every color in the code book.

The color features are encoded as histograms based on the visual words in a codebook. Feature contexts are mainly based on implicitly selected ROI. The encoded features are aggregated into one vector by pooling function to describe the region. Linear SVM is trained for colour recognition of vehicle images. Although in many cases nonlinear SVM generally outperforms linear SVM, it takes more time to train a model. Dominant color is displayed as the vehicle color.

F. Vehicle Speed Detection
In this work, to detect the speed of one vehicle is constantly tracked for M frames. During this tracking procedure, the system detects the speed of the tracked vehicle. The vehicle motion is small in every one frame interval. So the movement of a particular feature point is relatively small in consecutive frames. Distances between the feature point of this vehicle object and the feature point of vehicle object in the next frame are calculated. That is displacement of feature point is calculated. The relative displacement is speed of that particular vehicle.

Displacement of feature point from one to another frame is \( dx = x_1 - x_2 \) and velocity is the \( dx/t \). Where ‘t’ is the time taken for move the feature point.

G. Vehicle Counting
Set an independent counter at a particular frame of the video sequence. The counter value increments with the presence of feature point of every vehicle object in that particular frame. The number of vehicle at a particular time interval is detected.

IV. EXPERIMENTAL EVALUATION
The system performance is evaluating using extensive experiments. That are conducted on the images and the videos collected from urban roads. The proposed algorithm is implemented in MATLAB on a Windows 7 \( \times \) 32-based system. Here we divide the colours of vehicles into eight classes, including blue, yellow, green, red, gray, black, white, and cyan. Linear SVM is trained and used in this method for color classification. Since there is no other public benchmark for vehicle color recognition, then built two data sets for this experiments: a) a vehicle image data set; and b) a vehicle video data set. These data sets are collected from urban roads, where the images and videos are taken in the frontal view captured by a high-definition camera with the resolution of 1920 \( \times \) 1080. The collected data sets are very challenging due to the noise caused by haze, illumination variation, and over exposure. Many vehicle images of various categories, such as cars, truck, and bus are contains in the image data set. The recognition rate is used to evaluate the performance of image based color recognition system. It also defined the ratio between the correctly predicted properties of vehicle numbers and the totals. The video data set contains at least five pieces of surveillance videos. 10 frames per second is the frame rate of all videos, and the average video length is about 4-5 min. Then use an average confusion rate to evaluate the average performance in video sequences. If all the vehicles appearing in the frame are assigned to the correct colors speed and count, a frame is successfully recognized. Only the frames with vehicles are taken into account in the evaluation process and no other frames are used. The accuracy in vehicle counting and vehicle speed detection is also evaluated using video datasets. The accuracy of video-based vehicle detection systems relates to several factors: accurate segmentation and extraction of vehicle contours, effective shadow removal, illumination changes, vehicle occlusions and so on. The background color cannot be segmented fully and extracted correctly and its length and area are hard to obtain accurately, which leads to wrong recognition.

V. CONCLUSION
Different properties of multiple vehicle types are important for pavement design of traffic operations and traffic control. A novel video-based traffic data collection system for multiple vehicle types is developed in this work. From the urban road traffic videos or images, the colour and speed of every passing vehicle are recognised using image processing. Finally, the colour, count and mean speeds of multiple vehicle types are output. This system is very useful to analyse user behaviour. It is a main application field of Intelligent Transportation System.

REFERENCES


